CHAPTER 6

ENHANCED PROFICIENT RATE CONTROL DATAAGGREGATION-FAIR BANDWIDTHALLOCATION ALGORITHM (EPRCDA-FBA)

6.1 INTRODUCTION

An effective data aggregation technique is used in the prior work to present PRCDA-FBA, which maximizes the equitable usage of battery power across all participating nodes. Adaptivenetwork coding (Data augmentation) is used to reduce delays and energy use in datatransmission, leading to higher total network throughput. Network coding is done usingRLNC. The data packets supplied by a single node in one communication iteration areknown as the transmission frequency. A sensor nodes Generally speaking, the transmission frequency should not be higher than one packet every transmission cycle. A sensor node's transmission frequency should normally not exceed one packet each transmission cycle. Conversely, decrease in transmission frequency led to an increase in network channel capacity and an improvement in overall network throughput. By merging data for transmission to the next hop, the network coding technique reduces packet redundancy and boosts channel utilization in the network. An adaptive methodology that reduces packet dropping rate by integrating network coding with node data transmission is activated when congestion occurs.

Additionally, LSTM capable of learning long-term dependencies, enhance the bandwidth allocation of PRCDA-FBA. They have a time dimension that helps them to recognize patterns in data sequences. This task necessitates learning novel network behaviours while keeping track of historical data, therefore this property is of special relevance.The future bandwidth requirements of the path are predicted using the bandwidth consumed in previous events along with factors like packet drop rate, energy, packet priority, and packet latency.Despite the fact that data aggregation mechanisms cut down on energy and needless transmission. Overheating of energy-critical sensor nodes lowers network performance. The energy critical nodes have lower bandwidth utilizations, but power management is required to prevent overhearing at energy-critical sensor nodes.

As a result, EPRCDA-FBA is proposed to further save energy utilization and improve network life time. Overhearing requires a substantial amount of energy, resulting in localized node outages. The approach presented here is designed to guarantee that QoS requirements are satisfied by enhancing network resilience, lowering power-hungry nodes' energy consumption, and postponing data transfer.A primary concern with this protocol's rate management approach is the increased power consumption of the node.By using priority-based rate regulation, this predictive approach effectively contributes to deteriorating network performance.

It is proposed that EPRCDA-FBA be used to further reduce energy consumption and extend network life. Ensuring that QoS requirements are satisfied in terms of delayed data delivery, decreased energy consumption of energy-intensive nodes, and extended network lifespan is the initiatives main goal.This prioritybasedtechnique of regulatingdata transferrates takes intoconsideration thenodes spare processing capacity. Initially, the maximum node transmit power dip that may be tolerated without significantly reducing the packet delivery ratio is calculated using a prediction model.An energy combination is then used to build a priority of nodes for forwarding traffic classes of packets so as to prevent overhearing energy-critical nodes.

This prediction model is used by the nodes for two purposes. With this paradigm, a node can first establish a certain degree of connection quality, and then it can calculate how much power it can drop proportionately to a receiver. Second, the node can control the amount of overhearing that is broadcast to the neighbors that need energy at a given transmit power level.Overhearing can be identified by counting the number of packets received at the network layer, even though it usually occurs at the physical layer.To establish a connection between the forward network lifetime at the receiver and the broadcast power level at the emitter, At the receiving end, a prediction model is built because the power level of the broadcaster is a crucial factor in determining the quality of the link between two nodes.As a result, this algorithm effectively avoids the slowdown of anetwork.

6.2POWER CONTROL MANAGEMENT IN WSN

Gathering energy from environmental resources is a popular method used to ensure the long-term viability of WSNs. While it is true that harvesting energy from the environmenthas the potential to deliver an infinite lifespan, doing so also presents new design issuesfor preventing infrequent node failures. To establish a connection between the forward network lifetime at the receiver and the broadcast power level at the emitter, a prediction model is constructed at the receiving end. In the case of solar power harvesting, for instance, all nodesareaffectedbytheunpredictablediurnalandseasonalchangesinlightirradiation.

Additionally, the effect of shadowing from neighbouring barriers varies randomly throughout nodes. The use of thermal gradients, electromagnetic waves, and mechanical energy from vibrations as renewable energy sources is growing because they exhibit similar oscillations and has the ability to recharge low-power gadgets. Due to the sensing, communicating and processing operations at the nodes, energy consumption varies greatly. As the result, it is important to buildadaptive networking protocols that can protect against node failures thatregulate the amount of power used by sensor nodes in accordance with the charge level oftheir batteries Pal, Nasipuri(2019) proposed a system to limit the amount of power usedby nodes with limited energy resources, even if doing so requires the use of resourcesfromnodes withmoreflexibilityinthis regard.

When it comes to environmental monitoring, WSNs are often regarded because allnodes periodically send their sensor observations to one central hub.One example of a dynamic link-quality based routing protocol that creates multihop channels for sensor node interaction is the Collection Tree Protocol (CTP) (Gnawali et al., 2009). It was found that one of the most efficient methods of power management in WSNs is the coordinated use of sleep and waking periods by the sensor nodes' transceivers. This, however, necessitates time synchronization across thenetwork,whichaddsextracomplexityandlatency.

The elimination of the requirement for time synchronization allows for asynchronous duty-cycling of the sleep and waking cycles of the sensor radios, such as low-Power Listen (LPL).When there is low network traffic on huge networks, this is very beneficial.Low-Power Listening (LPL) allows receivers to operate at extremely low duty cycles while performing periodic scanning of the channel for radio frequency activity, thus facilitating power conservation.Every packet that is delivered has a lengthy preamble to ensure that the recipient is awake and aware when the packet arrives. However, in large-scale mesh sensor networks using asynchronous duty-cycling, overhearing is a major energy drain.In both of these investigations, numerous strategies, including adaptive duty-cycling and terminating unneeded receptions based on preamble information, have been implemented to address overhearing energy consumption.The proposedapproach of adaptive method is given in Figure 6.1.

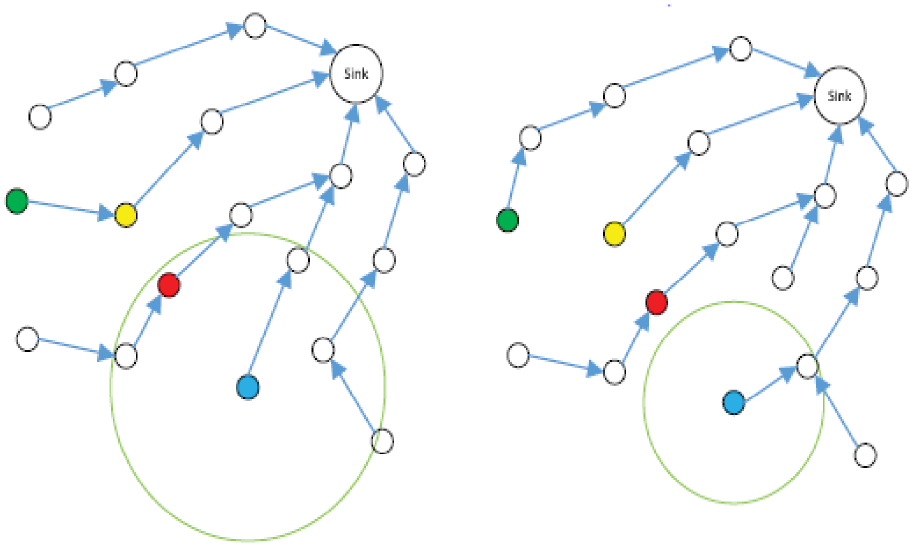

Figure 6.1 Illustration of Power Control and route adaptation for reducing over hearing at energy constrained node

A method that uses network-wide route modifications and coordinated transmission power regulation to lessen overhearing at nodes with severe energy constraints. It is assumed that the red node in this instance has less energy resources than the other nodes. It is adopted that route quality metrics, like the Collection Tree Protocol (CTP), which do not factor in energy considerations, are used for the initial route establishment.As seen in Figure 6.1(a) and (b), the black node reduces its transmit power and changes its direction, while the green node does the same. When combined, these changes reduce overhearing at red nodes.Observe, how transmissions from the adjacent blue and yellow nodes may be picked up by the red node. The red node overheats because it is close to the yellow node, which increases the transmission stress that the green node experiences. From the figure,the red node would gain from the suggested power control and routing mechanism intwo ways (b). To start, the red neighbor of the blue node uses transmit power regulationandroute adaptationtolimitbroadcastinterference.

If the path to the blue node is stretched as a result of this modification, the end-to-end delay might be prolonged.A green colour node changes its path by choosing a new parentin order to ease the load on the yellow node and increase the red nodes tolerance fornoise. Both of these modifications lessen workload at the red node and hence save power.

Theenergycriticalnodeshavelowerbandwidth utilizations,butpowermanagementis required topreventoverhearing atenergy-criticalsensornodes.Tofurtherreduceenergyconsumptionandprolongthelifespanofnetworks, EPRCDA-FBAisproposed.Becauseofthehighenergyrequirements of overhearing, individual nodes may go down.By reducing the energy consumption of energy-hungry nodes, improving network resilience and delaying data delivery, this technique guarantees that the quality of service (QoS) requirements are fulfilled.

6.3PROPOSED METHODOLOGY

For the EPRCDA-FBA algorithm, a Proficient Rate control strategy that considers energy is suggested. The main goal is to ensure that QoS requirements are met for longer network lifetimes, lower energy consumption of energy-hungry nodes, and delayed data delivery. A priority-based rate control mechanism used by this algorithm accounts for the nodes' excess power. First, the least amount of energy that a node may send without materially affecting the packet delivery ratio is determined using a prediction model.A priority of nodes for sending traffic classes of packets is then constructed using a combination of energy so as to prevent overhearing energy-critical nodes.

The nodes employ this prediction model for two reasons. A node can use this paradigm to first determine how much power it can proportionately reduce to a receiver while keeping a specific level of connection quality.Secondly, for a particular transmit power level, the node can determine the number of overhearing relayed to the energy-essential neighbors.Overhearing often manifests itself at the physical layer, but its impacts can be estimated at the network layer by counting the packets that were successfully received. It is helpful to develop a prediction model that links the broadcasters power level to the forward network lifetime of the receiver since the broadcasters power level has a significant influence on the link quality between two nodes. Following is one method for determining a networks PDR based on the log-normal shadowing model:

$$PDR = Prob[O_r(f) > \alpha] = Prob\ [O_t - O_l(f) > \alpha] \qquad (6.1)$$

$$= Prob\ [O_t - O_l(f) + X_\sigma > \alpha \qquad (6.2)$$

$$= Q\left(\frac{\alpha - O_t - \overline{O_l(f)}}{\sigma}\right) \qquad (6.3)$$

Given an assumed connection distance of d, the intended receiver signal threshold is represented by Or(f) and Ol(f), which represent the resumption and path loss at the receiver, respectively. It was represented the transmission power level. Xσ is a Gaussian random variable with a mean of zero and a standard deviation of σ. Xσ primarily represents a shadowing effects caused by fading and ambient noise at the receiver end, which produce small-scale signal variation. To create a new prediction model using measurements to calculate a function that connects transmit power and the packet delivery ratio(PDR). The function evolves throughout time to reflect the passage of time.

Subsequently, the transmitter sent out a bunch of data packets at G levels of power $L = \{l_1, l_2, \dots, l_n\}$, and the matching delivery percentages are$D = \{d_1, d_2, \dots, d_n\}$,to imitate the test link's corresponding function. The distribution of delivery ratios at various transmit power levels is represented by an approximately sigmoid error function. In Eq.(6.4) addressed as a result, the L-D relationship can be approximated as,

$$d_i = \frac{1}{1 + e^{-(x.l_i + y)}} \Rightarrow x.l_i + y = \ln\left(\frac{d_i}{1 - d_i}\right) = D_i \qquad (6.4)$$

To employ two vectors L and D to create the predictive model, where $L = \{l_1, l_2, \dots, l_n\}$, These characteristics are determined at the receiver end and communicated to the transmitter via beacon messages so that the transmitter can capture them. The Eq. (7.5) determines the matrix for these characteristics as given below:

$$\begin{bmatrix} l_1 & 1 \\ \vdots & \vdots \\ l_n & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} D_1 \\ \vdots \\ D_n \end{bmatrix} \Rightarrow \begin{cases} a = \frac{\sum D_i . \sum D_i - u . \sum D_i l_i}{\sum D_i . \sum D_i - u . \sum l_i^2} \\ b = \frac{\sum D_i - x . \sum l_i}{m} \end{cases} \qquad (6.5)$$

From the eq. (6.5), the co-efficients of x and y are calculated by fitting a linear regression curve.Because of the variations in time, the$D_i$and $l_i$values changes and thus the values of x and $y$are updated simantaneously.The pairs (l_i, D_i) are accumulated as process by the receiver. In their beacon messages, the transmitters include the actual transmit power levels (of respective data packets).

Data packets are given unique identifiers so that receivers, also known as overhearers, may monitor them and calculate the link-ETX (packet delivery ratio) at a particular power level.Each transmitters broadcast power and packet delivery ratio are carefully noted by the receivers (via transmission or overhearing) and entered into a table known as the Feedback Table (or FTable). Each neighbor'sFTable has the following information likex ϵ ψ_y,nodeID of x, power-level of x, PDR of x→y, link-ETX of x→y, a, b}.

A receiver runs the prediction model when it has sufficient confidence in a link, which is when it has acquired sufficient FTable data over a wide range of delivery ratio and transmit power levels and records the pair(x, y) . When j sends beacon messages, it concatenates the nodeIDs and their corresponding (x, y) pair from the FTable to the message.

The efficiency of this model improves as the number of (l_i, D_i) samples increases until it has enough information (or confidence) to execute this transmitter-associated model, it only broadcasts a and b at their default values. The receiver i then estimates the link quality of xy using the (x, y) pair at any power level between Eq.(6.3) and Eq.(6.4). The broadcaster i. (or NTable) also maintains a table called Neighbour Table. The NTable holds the following fields for each neighbour y ϵ $\psi_{x,}$ {nodeID of y, PDR of x→y, link-ETX of x→y, node-ETX of y, a, b}.Training parameters - TDR, RTT, packet ratio, traffic load intensity.

The EPRCDA-FBA algorithm is a useful power management model for reducing battery power and energy consumption. TheAlgorithm 6.1 outlines the steps involved in implementing the Enhanced Proficient Rate Control with Dynamic Adjustment - Feedback-based Approach (EPRCDA-FBA) for congestion control in network simulations.

Algorithm 6.1 : EPRCDA-FBA

Input: Node N

Output: Managed battery power

Step 1: Node has information to share

Step 2: Correlate the transmit power level

Step 3: Reduce traffic patterns using algorithm PRCDA-FBA

Step 4: Using the log-normal shadowing model

Step 5: Compute packet delivery ratio (PDR) of a link

$$PDR = Prob[O_r(f) > \alpha] = Prob\ [O_t - O_l(f) > \alpha]$$

Step 6: Assume that the transmitter sent a group of data packets at G power levels$L = \{l_1 , l_2, \dots , l_n\}$

Step 7: Set delivery ratios are found to be $D = \{d_1 , d_2, \dots , d_n\}$

Step 8: Find relationship between L and D can be approximated as

$$d_i = \frac{1}{1 + e^{-(x.l_i+y)}} \Longrightarrow x.l_i + y = \ln\left(\frac{d_i}{1-d_i}\right) = D_i$$

Step 9: Employ two vectors L and D, where $L = \{l_1 , l_2, \dots , l_n\}$ to generate the predictive model

Step 10: The coefficients a and b are determined using a linear regression curve-fitting method.

Step 11: Stores (D_i, l_i) in FTable Corresponding to S

Step 12: Broadcast (x, y, S) in beacons

Step 13: Store (x, y) in NTable corresponding to R.

Figure 6.2 provides a visual representation of the steps involved in the proposed PRCDA-FBA method, highlighting the sequence of operations.

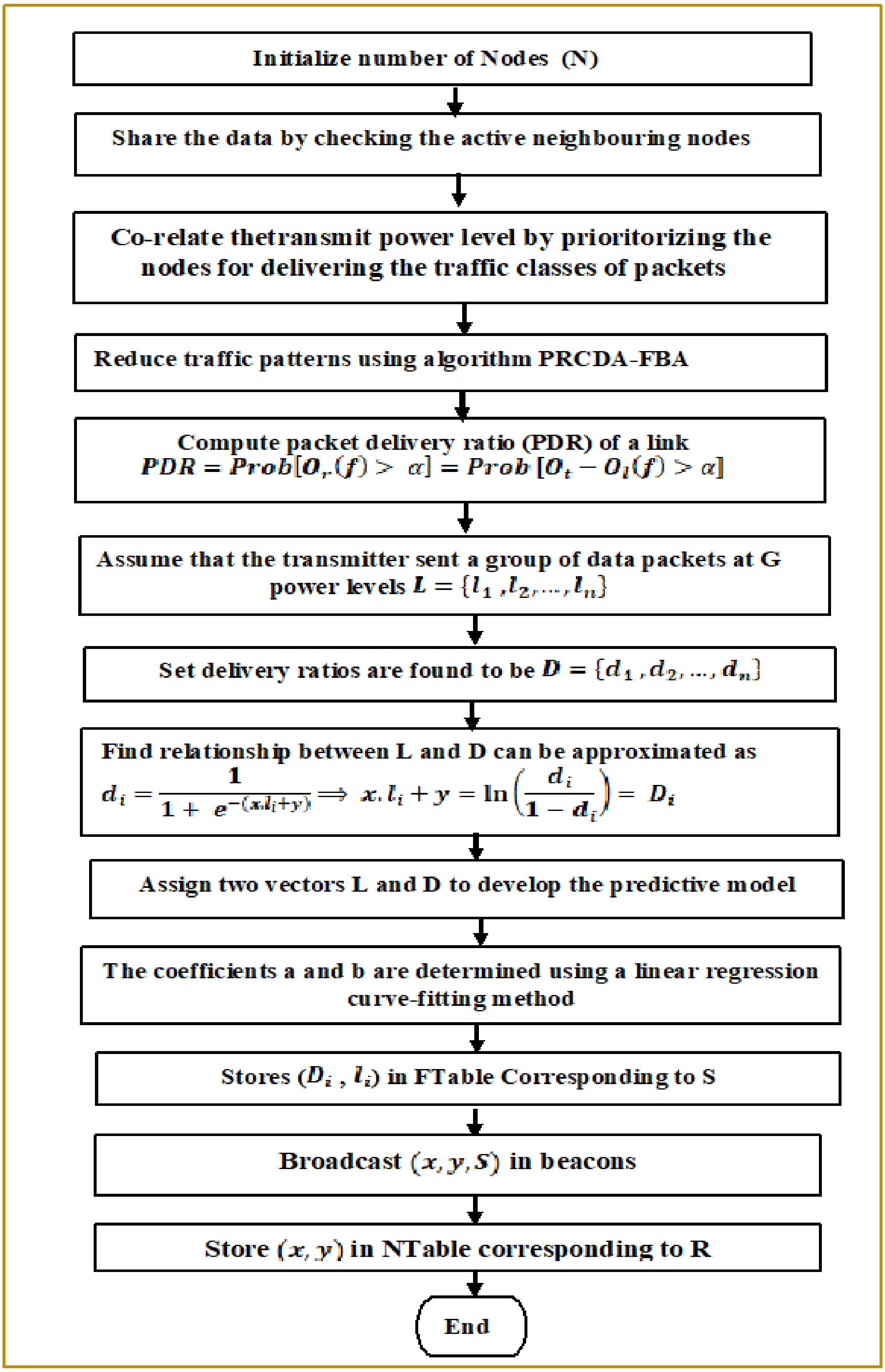

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Figure 6.2Flow Diagram of proposed PRCDA-FBA method

The EPRCDA-FBA algorithm represents a significant advancement in power management strategies for communication systems which states that there is a relationship between the power of the transmitters signal and the quality of the forward link to the receiver. The proposed algorithm effectively balances the trade-off between energy efficiency and communication reliability, leading to improved battery life and optimized power utilization.

6.4 SIMULATION RESULTS

The EPRCDA-FBA compared with the PRC, PRC-FBA, and PRCDA-FBA to determine the energy efficiency by the parameter metrics.

6.4.1 Throughput

The throughput of PRC, PRC-FBA, PRCDA-FBA andEPRCDA-FBA are compared with definite number of iterations. Table 6.1 provides thecomparison values of throughput for proposed EPRCDA-FBA with existing methods like PRC,PRC-FBA and PRCDA-FBAwiththe numberofiterations.

Table 6.1 Throughput Comparsion

Simulation time(sec)	PRC (Kbps)	PRC-FBA(Kbps)	PRCDA-FBA (Kbps)	EPRCDA-FBA (Kbps)
20	375	396	406	446
40	408	421	431	471
60	429	444	454	494
80	450	473	483	523
100	472	497	507	547
120	490	515	525	565

For several elapsed simulation durations (in sec), it was shown the throughput (in Kbps) for the PRC, PRC-FBA, PRCDA and EPRCDA-FBA approaches.It wasdemonstrated that EPRCDA-FBA had the highest throughput when compared to alternative methods.Thethroughput of EPRCDA-FBA was 10.15% higher than that of PRCDA-FBA, 8.11% higherthanthatof PRC-FBA and4.2%higherthanthatofPRCmethods,assumingasimulation time of 120 seconds. This was accomplished by giving each nodes share of the virtual queue's bandwidth a unique priority.From the Table 6.2 and 6.3, the resulting packet loss and end-to-end delay was indicative ofthroughput.

6.4.2 Packet Loss

The packet loss of PRC, PRC-FBA, PRCDA-FBA andEPRCDA-FBA was compared with definite number of iterations. Table 6.2 provided thecomparison values ofpacket loss for proposed EPRCDA-FBA with existing algorithmslike PRC,PRC-FBAandPRCDA-FBAwiththe numberofiterations.

Table 6.2 Packet Loss Comparsion

Simulation time(sec)	PRC (%)	PRC-FBA(%)	PRCDA-FBA(%)	EPRCDA-FBA(%)
20	4.4	3.2	2.9	1
40	6.4	5.5	4	2
60	10.6	9.1	7	3.1
80	15.1	13.8	10	6
100	19.5	17.6	16	11
120	25.2	23.7	20	17

It was shown the packet loss (in %) for the PRC, PRC-FBA, PRCDA and EPRCDA-FBA approaches at various simulation time (in sec). According to this research, EPRCDA-FBA outperforms rival techniques in terms of packet loss. For a duration of 120 seconds, Packet loss was decreased by 3.5% percentage when was compared to PRC techniques, 10.5% when compared to PRC-FBA and 17.3% when compared to PRCDA-FBA.Due to the use of virtual queues and fair distribution of bandwidth to all nodes for congestion management over the WSN, EPRCDA-FBA achieves the lowest possible packet loss.

6.4.3 End-to-End Delay

Table 6.3 provides a direct comparison of the end-to-end (E2E) delay in milliseconds for the proposed EPRCDA-FBA method and existing methods like PRC, PRC-FBA, and PRCDA-FBA, each with a fixed number of iterations, at various simulation times in seconds.

Table 6.3 E2E DelayComparison

Simulation time(sec)	PRC (ms)	PRC-FBA(ms)	PRCDA-FBA(ms)	EPRCDA-FBA(ms)
20	83	71	60	23
40	101	90	79	43
60	130	119	108	73
80	142	132	121	83
100	170	157	146	113
120	183	172	161	123

It was demonstrated that compared to other methods, EPRCDA-FBA exhibited the lowest end-to-end (E2E) delay. Specifically, after a 120-second simulation, EPRCDA-FBA achieved an E2E latency that was 9.5% shorter than that of PRCDA-FBA, 7.5% lower than PRC-FBA, and 5% lower than the overall PRC methods. This correlation indicates that the highest throughput and the least packet loss are associated with the lowest E2E delay.

6.4.4 Queue Size

Table 6.4 presents a comparison of the end-to-end (E2E) delay of PRC, PRC-FBA, PRCDA-FBA, and EPRCDA-FBA with a fixed number of iterations. It provides the average queue size (in packets) for the proposed EPRCDA-FBA and existing methods like PRC, PRC-FBA, and PRCDA-FBA at various points during the simulation.

Table 6.4 Queue Size Comparison

Simultion Time(sec)	PRC (Pkts)	PRC-FBA (Pkts)	PRCDA-FBA(Pkts)	EPRCDA-FBA(Pkts)
20	5	3	2.5	1
40	8	6	5.3	2
60	11	9	8.2	4
80	14	11	9.4	5
100	18	15	14.2	9
120	22	18	16	10

EPRCDA-FBA was found to achieve the lowest average queue length among the methods studied. In a 120-second simulation, EPRCDA-FBA reduced the average queue size by 34.4% compared to PRCDA-FBA, 26% compared to PRC-FBA, and 15.4% compared to PRC methods. Therefore, increasing the minimum queue length may reduce packet loss and end-to-end (E2E) latency. It was evident that EPRCDA-FBA enhances stability by maintaining the mean queue size at an optimal value.

6.4.5 Data Transfer Rate

Table 6.5 provides a comparison of the data transfer rate adjustment of PRC, PRC-FBA, PRCDA-FBA, and EPRCDA-FBA with a different number of iterations. It presents the data transmission rate adjustment values for the proposed EPRCDA-FBA and existing algorithms such as PRC, PRC-FBA, and PRCDA-FBA at various iterations during the simulation.

Table 6.5Data Transfer Rate Comparison

Simulation time(sec)	PRC (Pkts/s)	PRC-FBA (Pkts/s)	PRCDA-FBA (Pkts/s)	EPRCDA-FBA(Pkts/s)
20	68	72	74	80
40	64	67	69	75
60	60	63	65	71
80	57	60	63	69
100	54	57	59	65
120	51	54	57	63

t was demonstrated that the data transfer rate (in packets/sec) varied for the PRC, PRC-FBA, PRCDA-FBA, and EPRCDA-FBA methods across different simulation times. These findings highlight that the advanced rate adjustment and bandwidth distribution capabilities of EPRCDA-FBA enabled it to achieve the highest data transfer rate. Specifically, EPRCDA-FBA exhibited a data rate 10.2% higher than PRCDA-FBA, 8% higher than PRC-FBA, and 4% higher than PRC methods, assuming a simulation time of 120 seconds.Furthermore, it was observed that the data transfer rate gradually decreased as managed by EPRCDA-FBA compared to the initial transfer rate of the nodes. This adjustment allowed for appropriate distribution of highest priority traffic classes without congestion before the transfer rate was reduced.